State dependence and wage dynamics: a heterogeneous Markov chain model for wage mobility in Austria

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Abstract

The behaviour of individual movements in the wage distribution over time can be described by a Markov process. To investigate wage mobility in terms of transitions between quintiles in the wage distribution we apply a fixed effects panel estimation method suggested by Honoré and Kyriazidou (2000). This method of mobility measurement is robust to data contamination like all methods that treat fractiles. Moreover it allows for the inclusion of exogenous variables that change over time. We apply the estimator to a set of individual data form the Austrian social security records and find that disregarding unobserved heterogeneity greatly underestimates wage mobility. Simulated earnings profiles show that women are less mobile than men and have a tendency to be stuck in the lower part of the wage distribution.

Keywords: Wage mobility, Markov process, fixed effects panel estimation
Jel classification: C23, C25, J31, J60

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1 Introduction

The inequality of income and the persistence of low income are important social indicators. From the welfarist point of view the static picture of inequality in income in a single point in time can only be completed by considering the dynamics of the income distribution as well. Individual mobility in the income distribution gives an impression of the equality of opportunities in a society and it also informs about the income risks an individual faces by moving downwards in the distribution. During the 1980s and early 1990s increasing levels of wage inequality have been discovered in several OECD countries, particularly in the USA and UK (Levy and Murnane, 1992; Machin, 1998). This has generated much interest in wage mobility. An important issue in the discussion is whether wage mobility can at least partly offset the effects of cross-sectional inequality over the lifetime circle.

Wage mobility is usually measured at an aggregate level by calculating mobility indices. Common methods are to evaluate transition matrices of income states between two points in time or to examine the equalising effect of mobility on cross sectional wage inequality as the period of investigation is extended (see Fields and Ok, 1999, for an overview). Although the indices are helpful for the comparison of wage mobility between countries or population groups, their calculation does not allow for heterogeneity among individuals. The analysis remains on a descriptive level and it is impossible to examine the magnitude of the effects that certain personal characteristics have on wage mobility. Research following a different approach fits stochastic processes to the dynamics of earnings. Analyses of that kind frequently use adjusted earnings, which are corrected for time invariant individual characteristics (for example Buchinsky and Hunt, 1999; Dickens, 2000). Little research, however, can be found on models of wage mobility including time varying individual characteristics or unobserved heterogeneity.

Modelling unobserved heterogeneity might be important for studying wage mobility. For the dynamics of wages it is observed, like in many other situations, that an individual who has experienced an event in the past is more likely to experience that event in the future than an individual who has not experienced that event. Heckman (1981) discusses two explanations for this phenomenon. The first one is the presence of "true state dependence", in the sense that the lagged state enters the model in a structural way as an explanatory variable. The second explanation is that individuals differ in some unmeasured propensity to experience the event and this propensity is either stable over time, or the values of the propensity are autocorrelated. Heckman calls the latter source of serial correlation "spurious state dependence". Magnac (2000) presents a model distinguishing unobserved heterogeneity from state dependence in a study of transitions between labour market states.

Previous results on the evaluation of Austrian wage mobility indices in Hofer and Weber (2002) show that in an international comparison wage mobility is very low in Austria. By a comparison of different time periods wage mobility in Austria turns out to be relatively stable over time. Concerning different population groups, young workers and individuals who changed their employer are the most mobile groups.

In this paper we model the dynamics of transitions between wage quintiles as a first order Markov process, which is heterogeneous among individuals. We adopt a fixed effects multinomial logit estimation procedure designed by Honoré and Kyriazidou (2000), which is based on conditional likelihood maximisation (Chamberlain, 1984). We study wage dynamics for a large sample of Austrian employees who are observed between 1986 and 1998. The data set consists of a sample drawn form the Austrian social security records, which is the data source providing most accurate wage information over a long time horizon.

We contrast our Estimation results with models without unobserved heterogeneity and with homogeneous Markov processes. We find that the model without unobserved heterogeneity is strongly rejected and that wage mobility is much higher in the general model. Simulation results on the effects of estimated parameters show that women are less mobile than men. This is especially disturbing as women tend to remain in the lower part of the wage distribution. Further, changing the employer facilitates moving upwards in the distribution. Individuals show highest wage mobility in the early years of their earnings careers.

2 Model and Estimation Method

2.1 A model distinguishing true state dependence and heterogeneity

To describe transitions between categories of the wage distribution we adopt the latent propensity framework a la McFadden (1974). At each period, the latent variable y^*_{kit} describes the propensity level to be in state k out of states $0, ..., m$ for individual i at time t. In our case states are non-employment $k = 0$

and five wage quintiles $k = 1, ..., m$ with $m = 5$. We observe N individuals i at $T + 1$ points in time $t = 0, ...T$. The propensity function is determined by

$$y^*_{kit} = x_{it}\beta_k + \sum_{j=0}^{m} \gamma_{jk}\mathbf{1}\{y_{i(t-1)} = j\} + \alpha_{ki} + \epsilon_{kit} \tag{1}$$

where x_{it} is a vector of observable personal characteristics, $\mathbf{1}$ is the indicator function, $y_{i(t-1)}$ indicates the lagged state, $y_{i(t-1)} = j$ if the individual was in state j at $t - 1$, α_{ki} is an unobservable individual specific effect and ϵ_{kit} is an unobservable error term. Note that we model individual heterogeneity depending on the state and each individual has a specific propensity for each alternative. The parameters of interest to be estimated are $\beta = (\beta_0, \ldots, \beta_m)$ which give the influence of observed covariates on the propensity of being in each state and γ the coefficient on the lagged endogenous variable. The parameter γ is allowed to depend upon both the lagged state and the current state, so that there are in total m^2 feedback parameters and γ_{jk} is the feedback effect when the state j at $t - 1$ is followed by the state k at time t, where $j, k \in 0, ..., m$.

The link between the latent and the observed variables is given by the device that the observed state has maximal propensity:

$$y_{it} = k \text{ if } y^*_{kit} = \max_l (y^*_{lit})$$

As a consequence, if we assume that the underlying errors ϵ_{kit}, are independent across alternatives and over time conditional on (x_i, α_i, y_{i0}) and identically distributed according to the Type1 extreme value distribution, the probability of individual i of being in state k at time t, is given by

$$P(y_{it} = k | y_{i(t-1)} = j, x_i, \alpha_i) = \frac{\exp(x_{it}\beta_k + \gamma_{jk} + \alpha_{ki})}{1 + \sum_{l=1}^{m} \exp(x_{it}\beta_l + \gamma_{jl} + \alpha_{li})} \tag{2}$$

with $\alpha_i = (\alpha_{0i}, \ldots, \alpha_{mi})$ and $x_i = (x_{i0}, \ldots, x_{it})$. This implies that the transition matrix of this first order Markov process is heterogeneous between individuals. The model identification of β and γ is based on sequences of states where the individual switches between alternatives at least once during the periods 1 to $T - 1$. However, only $(m^2 - (2m - 1))$ feedback parameters are identified.

We apply the following identification restrictions:

$$\beta_0 = 0 \tag{3}$$

$$
\begin{aligned}
\gamma_0 &= (\gamma_{00}, \ldots, \gamma_{m0}) = 0 \\
\gamma_{0k} &= 0 \ \forall\, k = 1, \ldots, m \\
\alpha_{i0} &= 0 \ \forall\, i = 1, \ldots, N
\end{aligned}
$$

which means that all parameters with respect to the reference state $k = 0$ are equal to zero. In the empirical analysis we choose non-employment as reference group, as transitions from and to this state are different from transitions between wage quintiles.

It is worth noticing some special cases of the general model (1)

- No unobserved heterogeneity $\alpha_{ki} = \alpha_k \ \ \forall\, i = 1, \ldots, N$

  $$y^*_{kit} = x_{it}\beta_k + \sum_{j=0}^{m} \gamma_{jk}\mathbf{1}\{y_{i(t-1)} = j\} + \alpha_k + \epsilon_{kit} \tag{4}$$

  This is a model where no unobserved individual heterogeneity is present and hence it is of the form of a standard multinomial logit model. If unobserved heterogeneity is absent, this model yields consistent and efficient estimates of the transition parameters. If unobserved heterogeneity is however present in this model, the lagged state variables and the error terms ϵ_{kit} are not independent and the estimates are inconsistent. We use the comparison of the general model (1) with unobserved heterogeneity and the multinomial logit model (4) to perform a test for the presence of unobserved heterogeneity.

- No observed or unobserved heterogeneity $\alpha_{ki} = \alpha_k$ and $x_{it} = 0 \ \ \forall\, i = 1, \ldots, N$

  $$y^*_{kit} = \sum_{j=0}^{m} \gamma_{jk}\mathbf{1}\{y_{i(t-1)} = j\} + \alpha_k + \epsilon_{kit} \tag{5}$$

  This model is the standard first order Markov process in the absence of any heterogeneity. We note it here because this model is usually applied for the calculation of transition matrices like the one given in Table 2. Also mobility indices based on transition matrices are usually calculated based on this model. Evidently estimates of the transition parameters and transition probabilities are inconsistent if heterogeneity is present and the lagged state variables and the error terms ϵ_{kit} are not independent.

A further important issue is the interpretation of the parameters in the model.

It is convenient to begin with calculating the odds ratio of moving from state j to state k relative to a movement from the same origin to the reference state 0:

$$\frac{P(y_{it}=k|y_{i(t-1)}=j,x_i,\alpha_i)}{P(y_{it}=0|y_{i(t-1)}=j,x_i,\alpha_i)}=\exp(x_{it}\beta_k+\gamma_{jk}+\alpha_{ki})$$

A high value of α_{ki} indicates a high propensity of moving to quintile k as opposed to moving to non-employment, conditional on any lagged state j. The effect of the covariate x on the log odd's ratio is measured by β_k

$$\frac{\partial}{\partial x}\log\frac{P(y_{it}=k|y_{i(t-1)}=j,x_i,\alpha_i)}{P(y_{it}=0|y_{i(t-1)}=j,x_i,\alpha_i)}=\beta_k$$

and the effect of the covariate x on the log odd's ratio of moving from state j to k relative to moving from state j to state k' is given by the difference $\beta_k-\beta_{k'}$.

To remove the individual specific effects we can write

$$\frac{\frac{P(y_{it}=k|y_{i(t-1)}=j,x_i,\alpha_i)}{P(y_{it}=0|y_{i(t-1)}=j,x_i,\alpha_i)}}{\frac{P(y_{it}=k|y_{i(t-1)}=0,x_i,\alpha_i)}{P(y_{it}=0|y_{i(t-1)}=0,x_i,\alpha_i)}}=\exp(\gamma_{jk}) \tag{6}$$

and it becomes easier to interpret the parameter γ_{jk}. Because the expression in (6) is not heterogeneous between individuals, it is the object of interest for measuring true state dependence. The expression gives the probability of moving from state j to state k instead of moving from state j to the reference state, relative to the probability of moving to k from state 0 instead of remaining in the reference state 0. If γ_{jk} is positive, the odds of being in state k with respect to state 0 when the lagged state is j are larger than when the lagged state is 0. Like before it is obvious that the effects of lagged states j and j' on the probability of moving to state k relative to non-employment can be measured by the difference of $\gamma_{jk}-\gamma_{j'k}$.

2.2 Conditional Maximum Likelihood Estimation

An important issue in panel estimation is if the individual effects are modelled as fixed or random. The latter is more common (Arellano and Honore, 2001) even though the specification of the distribution function of random effects is a delicate issue. In nonlinear models the numerical implementation of a random effects specification is also complicated by the evaluation of multiple integrals. For these reasons we model individual effects as fixed.

The individual fixed effects parameters α_{ik} in the general model (1) cannot be estimated consistently. Unlike in linear models the problem of incidental variables cannot be overcome by differencing. The idea applied by Chamberlain (1984) for fixed effects logit estimation was to derive a set of conditional probabilities that do not depend on the individual effects. Honoré and Kyriazidou (2000) pick up this approach and present a method for the estimation of panel data fixed effects discrete choice models when the explanatory variable set includes strictly exogenous variables, lags of the endogenous dependent variable as well as unobservable individual specific effects. Their estimation method is also extended to the case of multinomial discrete choice variables, and so covers our model for wage mobility.

Honoré and Kyriazidou (2000) regard events where the state variable y switches from say state k to state l or reverse between two points in time, say s and t with $1 \leq t < s \leq T-1$. Conditional on such a switch and on the constancy of the explanatory variables in the following periods $x_{i(t+1)} = x_{i(s+1)}$, the probabilities of the events are independent of the individual effects. Defining the binary variable $y_{hit} = 1$ if the individual is in state $h \in \{0, 1, \ldots, m\}$ in period t and zero otherwise, estimation can be based on the maximisation of the likelihood function

$$
\begin{aligned}
L \; = \; & \sum_{i=1}^{N} \sum_{1 \leq t < s \leq T-1} \sum_{k \neq l} \mathbf{1}\{y_{kit} + y_{kis} = 1\} \mathbf{1}\{y_{lit} + y_{lis} = 1\} \\
& \mathbf{1}\{x_{i(t+1)} = x_{i(s+1)}\} \ln \frac{\exp(D_1)}{1 + \exp(D_1)} \mathbf{1}\{s - t = 1\} \\
+ & \sum_{i=1}^{N} \sum_{1 \leq t < s \leq T-1} \sum_{k \neq l} \mathbf{1}\{y_{kit} + y_{kis} = 1\} \mathbf{1}\{y_{lit} + y_{lis} = 1\} \\
& \mathbf{1}\{x_{i(t+1)} = x_{i(s+1)}\} \ln \frac{\exp(D_2)}{1 + \exp(D_2)} \mathbf{1}\{s - t > 1\}
\end{aligned}
\tag{7}
$$

with

$$
\begin{aligned}
D_1 \; = \; & (x_{it} - x_{is})(\beta_k - \beta_l) + \gamma_{y_{i(t-1)},k} + \gamma_{kl} + \gamma_{l,y_{i(s+1)}} \\
- \; & \gamma_{y_{i(t-1)},l} - \gamma_{lk} - \gamma_{k,y_{i(s+1)}}
\end{aligned}
$$

and

$$
\begin{aligned}
D_2 &= (x_{it} - x_{is})(\beta_k - \beta_l) + \gamma_{y_{i(t-1)},k} + \gamma_{k,y_{i(t+1)}} + \gamma_{y_{i(s-1)},l} + \gamma_{l,y_{i(s+1)}} \\
&- \gamma_{y_{i(t-1)},l} + \gamma_{l,y_{i(t+1)}} + \gamma_{y_{i(s-1)},k} + \gamma_{k,y_{i(s+1)}}
\end{aligned}
$$

In the objective function above we impose the restrictions given in (3). The method requires at least four periods of observations since there must be some variability between the dates 1 and $T-1$. Stable histories, where the same state is occupied between 1 and $T-1$ do not contribute to the likelihood.

For every contribution to the likelihood function the state at two different points in time, the state in the periods before and afterwards and the values of the independent variables at these dates are important. Therefore the method can be interpreted as collecting similar histories of states and covariates, which make similar contributions to the likelihood. In contrast the estimation of the multinomial logit, model (5), corresponds to the estimation of the pooled data, neglecting the panel structure or individual histories.

The method allows only for time varying exogenous variables x with $P((x_{it} - x_{is}) = 0) > 0$. For this reason time dummies are excluded. We model age effects on wage mobility by defining dummy variables for age groups. Further no constant can be estimated in the model and therefore it is impossible to calculate the probabilities in the transition matrix with the estimated parameters; only odd's ratios like (6) can be given.

3 Data

We use a random sample drawn from the social security records in Austria. Our sample contains data on the social status of the individuals for every day covering the years 1986 to 1998. The social security authority collects detailed information for all workers in Austria, except for self-employed, civil servants and marginal workers.

There are major advantages of using such administrative data compared to the analyses based on surveys. First, there is no outflow apart from death and migration and inflow to the sample is random. Hence sample attrition, which is often considerable in longitudinal surveys, is not an issue in administrative data. Another advantage is that one gets a highly reliable measurement of income of individuals, because the recall of individuals regarding their incomes is unlikely to be better than the information from the social security authority.

A final advantage is that administrative data sets are often very large. The total sample contains daily information on about 73,000 persons, who have been in the labour force at least for one day between 1986 and 1998.

As the data are collected for social security reasons there are several shortcomings for empirical analysis. Earnings data are top censored because of the contribution assessment ceiling in the social security system. The sample we use for the analysis contains at most 15% censored wage observation per year. Thus we avoid problems with top censoring by using wage quintiles. Further, the number of observable worker characteristics is rather scarce, we have no information on schooling, working time and family affiliation. Because of the lack of information on working time, we cannot calculate wage rates. In our analysis wage mobility is examined in terms of monthly earnings. The lack of information on working time is important mainly for women, as part-time work is quite unusual for men in Austria.[1]

As a measure for income we use the gross monthly wage on May 31st of each year. Wages are categorised according to the quintiles of the yearly wage distribution. Individuals with zero wage income on May 31st fall into the category non-employed. Studying wage categories instead of continuous wage data avoids problems with top coding of wage information in the data set.[2] Moreover, methods relying on transitions between wage categories are robust against data contamination (Cowell and Schlüter, 1998).

From the sample we exclude all individuals from the sample who have zero earnings throughout the whole period and who are younger than 16 in 1998 and older than 64 in 1986. We are only interested in analysing movements within the wage distribution. Transitions form education into the labour force or transitions to retirement should therefore be not considered. For any individual over the age of 55 we define a series of observations in state non-employment which reaches the end year 1998 as retirement. Analogously for an individual under the age 27 we define a series of non-employment observations which starts in the first year (1986) as education. Those observations are excluded from the estimation. The reductions leave an unbalanced panel of 43,078 (18,422 female) workers.

Motivated by the results in Hofer and Weber (2002) we include four age categories and the number of employers as time varying covariates in the estimation

[1]The share of part-time work 1990 was 20% for women and 1.5% for men; it was rising during the 1990's.

[2]A disadvantage of studying quintiles is of course that the distance of the move between categories is not taken into account in the calculations.

procedure and all the analysis is conducted separately for men and women.

A list of descriptive statistics is given in Table 1. We notice that the distribution among wage quintiles is different for men and women. Men are rather to be found in the upper part of the wage distribution. In the top quintile we find 23% of all male observations but only 6% females. The picture is reversed at the bottom, where women are dominant. This can at least partly be explained by the inclusion of part-time working women in the sample. A matrix of yearly transitions between wage categories is given in Table 2. At a first glance persistence seems to be highest in the top quintile for both sexes. Men, however, move out of the bottom wage quintiles more quickly than women.

4 Results

Estimation results of the general model (1) are given for women and men in Tables 3 and 4, the period in which transitions are observed being one year.[3] Results from estimation of the pooled multinomial logit model (4) with no unobserved heterogeneity are given in Tables 5 and 6.

To contrast the pooled estimation (observed heterogeneity only) and the fixed effects panel estimation, it is useful to construct a Hausman test statistic testing the hypothesis that there is no unobserved heterogeneity. Tables 5 and6 present consistent and efficient estimates under the null hypothesis and estimates in Tables 3 and 4 are consistent under the null and the alternative. The null hypothesis is strongly rejected. The test statistic is equal to 56,099 for female results (61,900 for male results) and is under the null hypothesis distributed as $\chi^2(45)$.

From comparing the feedback parameters γ in the models with and without unobserved heterogeneity, we note that the diagonal elements are lager in the model neglecting unobserved heterogeneity. Mobility estimated by common indices like the average number of moves, or the trace of the transition matrix is underestimated. This might explain the results in Hofer and Weber (2002), where Austrian wage mobility is found to be extremely low in an international comparison. Low Austrian wage mobility indices might be due to individual heterogeneity and spurious state dependence.

If we turn to the covariates in Tables 3 and 4 we notice that an extra employer raises the probability of moving to each wage quintile as compared to moving

[3] Estimation routines in GAUSS are available upon request.

to non-employment. The estimates are increasing over quintiles, thus changing the employer helps to move upwards in the wage distribution.

We estimated the effects of three age groups (<25 years, 25 to 29 years and 30 to 34 years) as we assume that higher aged individuals show less mobility than young ones. Indeed the parameter estimates are highest for the youngest group, who are most likely to move to any quintile compared to moving to non-employment. For all age groups it is most likely to move to the bottom wage quintile, but the differences among parameters for the different quintiles are highest for the youngest individuals.

Simulations

The interpretation of the transition parameters is not straight forward but complicated by odd's ratio expressions like (6). In addition we would like to compare the effects of the estimated parameters for men and women. For these tasks we use a simulation approach. The idea is to design artificial individuals with special unobserved and observed properties and to investigate their simulated earnings profiles.

We begin with choosing the unobserved propensity of being in each quintile with respect to non-employment $\alpha = (\alpha_1, \ldots, \alpha_5)$. We consider one individual with high propensity to move up in the wage distribution (where α_1 is small compared to α_5), one with high propensity for the lower part of the distribution (where α_1 is large compared to α_5) and one who is indifferent between the wage quintiles ($\alpha_1 = \ldots = \alpha_1$).[4] For these individuals we choose 3 different starting ages (20 years, 30 years and over 35 years) and employer careers (the same employer over the total period employer changes every two years). For each individual female and male profiles are contrasted.

We generate earnings profiles by calculating the probability distribution over states in each year and choosing the state nearest to the expected value as the state of the current year. In period $T = 0$ all individuals start at quintile 1, to display a maximum of movements in the profiles. This process is run iteratively over 15 years and the resulting earnings profiles are displayed graphically in Figures 1 to 4.

It should be stressed that this method cannot give evidence for the development of earnings for some representative individual in the sample, as the values for α are taken ad hoc and not results from an estimation procedure. The only

[4]The constant term estimates in the multinomial logit model give an approximation for the magnitude of the chosen α values.

use of the graphical results is in simplifying the interpretation of the estimated parameters.

Now let us turn to the graphical results. Figure 1 shows earnings profiles for an individual with low propensity of moving to the upper wage quintiles, that means α is set to $\alpha = -(1, 1.5, 2, 2.5, 3)$. The pictures on the left show women with different ages in the starting year. Male equivalents are shown at the right hand side. For a 20 year old individual of either sex the unconditional mean given by the Markov process in the starting year would be wage quintile 2. If a woman starts in quintile one and never changes her employer she will not be able to approach the unconditional mean because of the high persistence parameter in the first quintile. If she changes the employer frequently, however, she moves upwards in the wage distribution. A man starting from the same position will approach the mean value after 6 years even if he does not change the employer. His upward movement in the wage distribution in case of employer changes is quicker than for females, with one step per employer change.[5] For older individuals the unconditional mean position in the distribution shifts to quintile 3 (women 30 years) or quintile four. Starting from wage quintile one makes it impossible to approach these mean values, only employer changes facilitate upward moves in the wage distribution. Again men move up quicker than women and they move farther in the case of no employer changes.

Next, Figure 2 shows individuals who are indifferent between quintiles in the wage distribution with $\alpha = -(1, 1, 1, 1, 1)$. The unconditional mean positions shift to wage quintile four or five. If we look at the youngest individuals we see that women without employer changes move in the same way as men. Both are not able to approach the unconditional mean by one quintile within 15 years. Men changing the employer move faster than women. Comparing higher aged individuals we find that men are able to move further than women with only one employer. Again men move faster in case of employer changes.

In the following Figure 3 we observe individuals who have a positive propensity of moving towards the top of the wage distribution. We choose $\alpha = -(3, 2.5, 2, 1.5, 1)$ and the unconditional mean position is quintile 5 for every individual. We now observe everyone to move out of the bottom wage quintile within a few periods. Employer changes support only younger individuals. Advantages of men over women vanish for higher ages.

[5] Employer changes every two years are a very dynamic scenario. The average number of employer changes per individual over twelve years is two in the sample, only one per cent of individuals changes their employer more than five times.

5 Conclusion

In this paper wage dynamics, measured by transitions between quintiles in the wages distribution, is modelled as a first order Markov process with heterogeneous individuals. Transition parameters are estimated in a fixed effects multinomial logit framework based on conditional likelihood maximisation. For the empirical analysis we use highly accurate individual wage data over a long time horizon from Austrian administrative sources.

The use of the method is supported by its robustness against data contamination and the top coding of wage information in the data set. Besides there is evidence for the calendar-time constancy of wage mobility in Austria (Hofer and Weber, 2002), which leads to a Markov process with non time-varying parameters. Because of the lack of information on several personal characteristics, like education, it is important to model unobserved heterogeneity and to distinguish between true and spurious state dependence. The use of a fixed effects estimation procedure is vindicated by the argument that the estimation of transition parameters is robust to any specification of the distribution of unobserved heterogeneity.

Results show that controlling for observed heterogeneity only is rejected against the alternative with unobserved heterogeneity. Moreover disregarding unobserved heterogeneity underestimates wage mobility, which contributes to explain low mobility indices found for Austria (Hofer and Weber, 2002). The examination of simulated wage profiles shows that women are less mobile than men. This is especially disturbing as women tend to remain in the lower part of the wage distribution. Our results give the impression that, even conditional on individual heterogeneity, there exist huge barriers for women to move out of the lower part of the wage distribution.

There are several ways in which the research issues in this paper can be extended. There are arguments that the large effects of unobserved heterogeneity on transition parameters may be due to heterogeneity of transitions themselves between individuals. Meaning that the dynamics of the Markov process are higher than one. Another attempt might be the estimation of the distribution of the unobserved heterogeneity parameters by non-standard methods like Markov chain Monte Carlo sampling.

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Table 1: Descriptive Statistics

	Women Mean	Std. Dev.	Men Mean	Std. Dev.
Non-employment	0.25		0.16	
Quintile 1	0.30		0.06	
Quintile 2	0.18		0.15	
Quintile 3	0.12		0.19	
Quintile 4	0.09		0.21	
Quintile 5	0.06		0.23	
Number of employers	1.44	0.95	1.59	1.06
Age (years)	37.37	10.46	38.23	10.45
Age < 25	0.13		0.09	
Age 25 to 29	0.15		0.15	
Age 30 to 34	0.15		0.17	
Observations	190,406		261,670	
Individuals	18,422		24,656	

Table 2: Estimated transition probabilities, yearly transitions, no heterogeneity

Women

Destination state	No income	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Origin state						
No income	0.777	0.150	0.040	0.018	0.011	0.005
Quintile 1	0.109	0.801	0.076	0.011	0.004	0.000
Quintile 2	0.078	0.060	0.751	0.102	0.007	0.001
Quintile 3	0.064	0.011	0.075	0.734	0.114	0.003
Quintile 4	0.053	0.004	0.008	0.061	0.800	0.074
Quintile 5	0.042	0.001	0.001	0.004	0.047	0.904

Men

Destination State	No Income	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Origin state						
No income	0.753	0.067	0.079	0.049	0.031	0.020
Quintile 1	0.187	0.602	0.166	0.032	0.011	0.002
Quintile 3	0.085	0.038	0.681	0.174	0.019	0.002
Quintile 4	0.047	0.006	0.084	0.717	0.141	0.004
Quintile 5	0.033	0.002	0.008	0.088	0.779	0.091
Quintile 6	0.023	0.001	0.001	0.003	0.053	0.919

NOTE: number of observations 261670 males, 190406 females.

Table 3: Estimated parameters from transition model with unobserved heterogeneity, Women, yearly transitions

Destination State	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Origin state					
Quintile 1	2.836	2.299	1.482	0.744	-0.031
	(0.031)	(0.045)	(0.080)	(0.145)	(0.333)
Quintile 2	1.250	3.435	3.011	1.811	1.266
	(0.041)	(0.051)	(0.066)	(0.111)	(0.261)
Quintile 3	0.097	1.977	3.983	3.436	2.189
	(0.081)	(0.061)	(0.074)	(0.095)	(0.190)
Quintile 4	-1.002	0.481	2.312	4.370	4.018
	(0.189)	(0.109)	(0.086)	(0.107)	(0.166)
Quintile 5	-0.743	-1.242	0.962	2.461	4.706
	(0.284)	(0.361)	(0.186)	(0.130)	(0.180)
Number of employers	1.037	1.172	1.312	1.383	1.805
	(0.034)	(0.046)	(0.065)	(0.092)	(0.148)
Age < 25	2.085	1.309	1.348	0.735	-0.279
	(0.156)	(0.194)	(0.240)	(0.310)	(0.513)
Age 25 to 29	0.882	0.332	0.600	0.419	-0.954
	(0.115)	(0.150)	(0.187)	(0.237)	(0.390)
Age 30 to 34	0.363	-0.154	0.047	-0.293	-0.870
	(0.082)	(0.111)	(0.133)	(0.164)	(0.251)
number of cases	114206				
number of individuals	14347				
mean log Likelihood	-0.257				

NOTE: fixed effects logit model estimated with conditional ML, T=12, standard errors are in parentheses.

Table 4: Estimated parameters from transition model with unobserved heterogeneity, Men, yearly transitions

Destination State	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Origin state					
Quintile 1	2.303	1.381	0.722	0.021	-0.607
	(0.047)	(0.047)	(0.079)	(0.138)	(0.303)
Quintile 2	1.032	2.529	2.307	1.099	0.808
	(0.048)	(0.040)	(0.043)	(0.073)	(0.182)
Quintile 3	0.730	1.664	3.383	2.948	1.566
	(0.083)	(0.045)	(0.047)	(0.055)	(0.113)
Quintile 4	0.048	0.675	2.528	4.091	3.762
	(0.143)	(0.074)	(0.052)	(0.060)	(0.082)
Quintile 5	0.277	0.005	1.151	3.042	4.890
	(0.211)	(0.203)	(0.101)	(0.071)	(0.091)
Number of employers	0.517	1.117	1.453	1.671	2.114
	(0.033)	(0.029)	(0.035)	(0.043)	(0.063)
Age $<$ 25	2.424	1.976	1.342	0.844	0.100
	(0.236)	(0.184)	(0.183)	(0.201)	(0.250)
Age 25 to 29	1.007	1.125	0.938	0.636	0.026
	(0.197)	(0.152)	(0.149)	(0.161)	(0.185)
Age 30 to 34	0.497	0.562	0.561	0.508	0.273
	(0.152)	(0.110)	(0.107)	(0.116)	(0.133)
number of cases	140511				
number of individuals	18296				
mean log Likelihood	-0.347				

NOTE: fixed effects logit model estimated with conditional ML, T=12, standard errors are in parentheses.

Table 5: Estimated parameters from pooled transition model (only observed heterogeneity), Women, yearly transitions

Destination State	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Origin state					
Quintile 1	3.149	2.033	1.079	0.624	-0.570
	(0.018)	(0.028)	(0.054)	(0.083)	(0.215)
Quintile 2	0.956	4.722	3.732	1.662	0.613
	(0.032)	(0.029)	(0.041)	(0.079)	(0.183)
Quintile 3	-0.520	2.654	5.903	4.527	1.640
	(0.072)	(0.042)	(0.043)	(0.054)	(0.147)
Quintile 4	-1.296	0.561	3.499	6.515	4.864
	(0.125)	(0.095)	(0.056)	(0.055)	(0.080)
Quintile 5	-2.128	-1.401	0.898	3.704	7.367
	(0.247)	(0.306)	(0.157)	(0.078)	(0.083)
Number of employers	0.295	0.314	0.256	0.253	0.240
	(0.009)	(0.011)	(0.014)	(0.017)	(0.026)
Age < 25	0.513	0.880	0.887	0.614	-0.609
	(0.024)	(0.030)	(0.039)	(0.059)	(0.165)
Age 25 to 29	-0.669	-0.501	-0.290	-0.271	-0.532
	(0.024)	(0.029)	(0.035)	(0.044)	(0.076)
Age 30 to 34	-0.482	-0.523	-0.398	-0.415	-0.572
	(0.023)	(0.029)	(0.036)	(0.043)	(0.064)
White collar	-0.064	0.316	0.999	1.721	2.316
	(0.016)	(0.020)	(0.028)	(0.044)	(0.102)
Constant	-1.479	-3.022	-4.452	-5.544	-6.752
	(0.019)	(0.028)	(0.042)	(0.061)	(0.121)
number of cases	190406				
number of individuals	18422				
mean log Likelihood	-0.146				

NOTE: multinomial logit estimation, T=12, the reference state is non-employment, standard errors are in parentheses.

Table 6: Estimated parameters from pooled transition model (only observed heterogeneity), Men, yearly transitions

Destination State	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Origin state					
Quintile 1	2.955	1.511	0.505	0.103	-0.889
	(0.027)	(0.032)	(0.053)	(0.082)	(0.179)
Quintile 2	1.026	3.758	3.037	1.437	0.047
	(0.036)	(0.025)	(0.030)	(0.049)	(0.114)
Quintile 3	-0.050	2.397	5.168	4.133	1.292
	(0.062)	(0.030)	(0.030)	(0.036)	(0.080)
Quintile 4	-0.781	0.553	3.520	6.269	4.692
	(0.101)	(0.056)	(0.035)	(0.036)	(0.046)
Quintile 5	-1.027	-0.893	0.660	3.927	7.060
	(0.135)	(0.126)	(0.081)	(0.043)	(0.046)
Number of employers	0.263	0.251	0.196	0.160	0.089
	(0.009)	(0.008)	(0.009)	(0.010)	(0.013)
Age < 25	1.117	1.430	1.250	1.151	0.547
	(0.031)	(0.027)	(0.030)	(0.037)	(0.067)
Age 25 to 29	0.068	0.269	0.257	0.376	0.362
	(0.031)	(0.025)	(0.025)	(0.029)	(0.039)
Age 30 to 34	-0.143	-0.011	-0.028	0.038	0.050
	(0.032)	(0.025)	(0.025)	(0.027)	(0.035)
White collar	-0.258	-0.504	-0.255	0.302	1.509
	(0.025)	(0.021)	(0.020)	(0.021)	(0.027)
Constant	-2.373	-2.266	-2.818	-3.529	-4.611
	(0.026)	(0.023)	(0.026)	(0.033)	(0.045)
number of cases	261670				
number of individuals	24656				
mean log Likelihood	-0.209				

NOTE: multinomial logit estimation ,T=12, the reference state is non-employment, standard errors are in parentheses.

Figure 1: Simulated wage profiles $\alpha = -(1, 1.5, 2, 2.5, 3)$

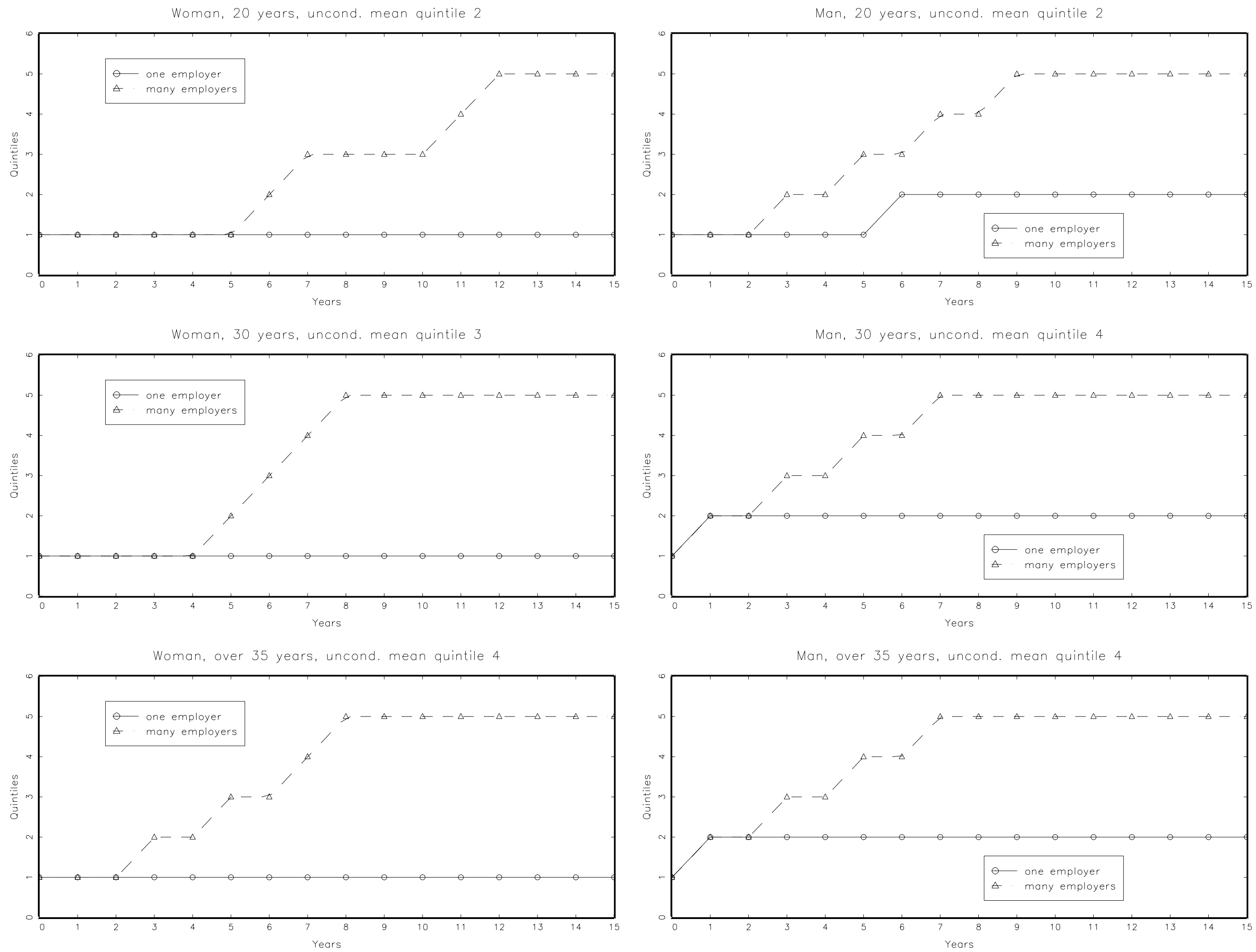

Figure 2: Simulated wage profiles $\alpha = -(1, 1, 1, 1, 1)$

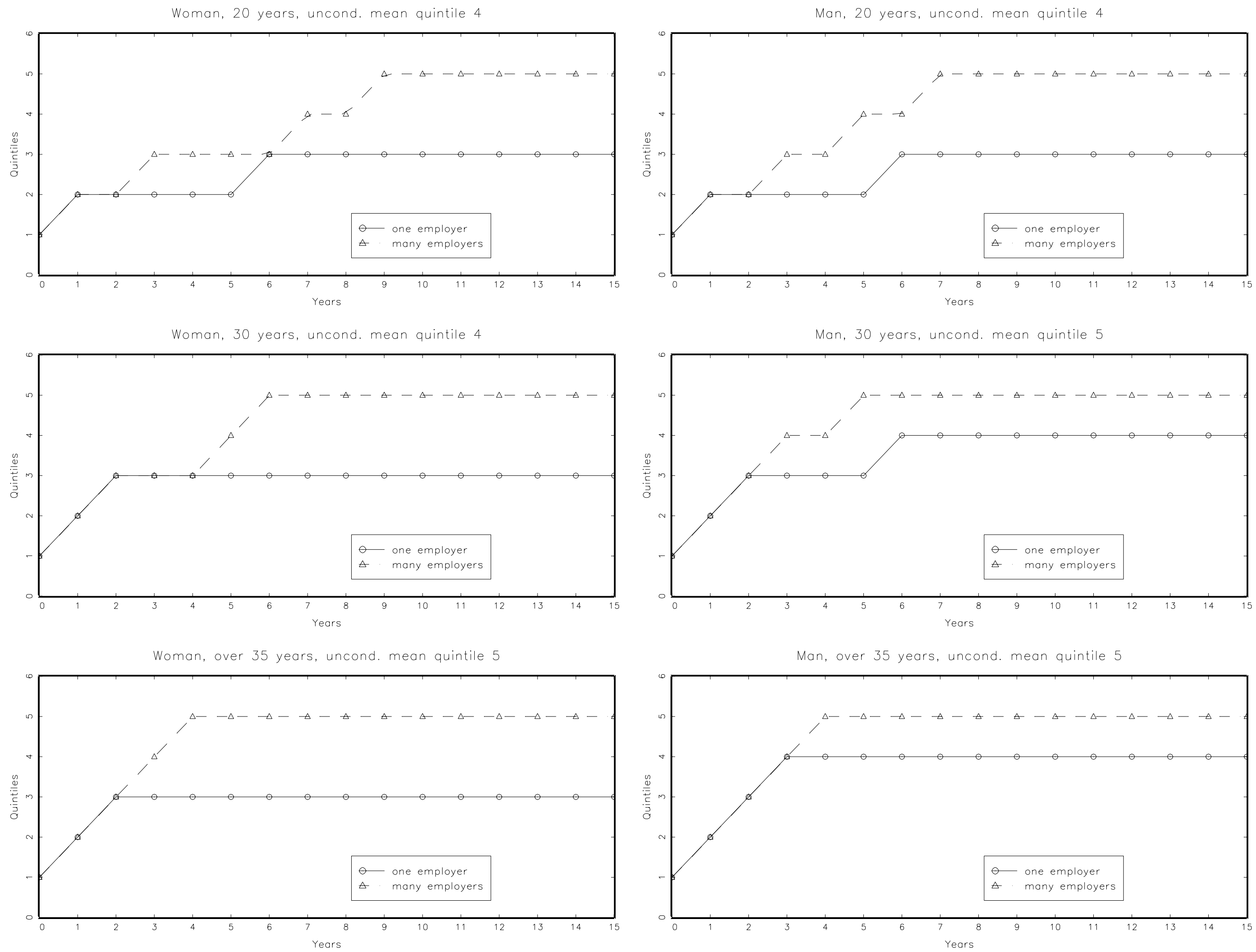

Figure 3: Simulated wage profiles $\alpha = -(3, 2.5, 2, 1.5, 1)$